# Participation in Multiple-Peril Crop Insurance: Risk Assessments and Risk Preferences of Cranberry Growers

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To investigate the poor participation rate of cranberry growers in the multiple-peril crop insurance program, a sample of 15 Massachusetts growers was interviewed. According to their risk preferences, a much greater proportion of growers should have insured, than actually did. A possible solution is to match the distribution used by the insurer closer to that believed by the grower. Adjusting each grower's historical yield series for trend brought the historical and subjective mean yields much closer. However, an aggregate test found the effect of adjustment to be insignificant, implying that the avenue for increased participation lies elsewhere.

Willingness to purchase crop insurance depends on the inherent riskiness of crop production, the grower's risk preference, and the size of the premium. Specifically, the purchase decision is governed by how the grower perceives the risk and how well it appears to match the risk assessment implicit in the insurance coverage offered. If a farmer is sufficiently averse to risk in crop income, and if crop insurance provides risk reduction, the farmer would be expected to participate.

In this article several potential influences on the participation rate of cranberry growers are examined. The study attempted to measure the subjective risk assessments and degrees of risk aversion of a sample of growers, analyze the insurer's assessment of risk and compare it with the growers' views, and determine the conditions under which insurance participation would be optimal. The approach is similar to that of Zering, McCorkle, and Moore. The analyses differ in that Zering *et al.* dealt with multicrop farms; the present study focused on those that grow a single crop. It also put more emphasis on the different implications of subjective and historically-based yield assessment.

Very few other studies have combined the measurement of risk and decision maker preferences in order to make participation predictions. King and Oamek made normative predictions when they used historical prices and yields rather than subjective assessments. Lee, Brown, and Lovejoy predicted whether farmers would adopt minimum tillage based on objective or subjective yield estimates and compared the results with actual behavior, but without eliciting the farmer's risk preferences.

## Cranberry Crop Insurance

The cranberry industry was selected for the study because it had been the subject of a pilot program to extend crop insurance to a wider range of crops. The Federal Crop Insurance Act of 1980, which eliminated the Disaster Payments Program, proposed Multiple-Peril Crop Insurance (MPCI) as the major form of disaster protection for farmers. The Act authorized the Federal Crop Insurance Corporation to insure producers of any agricultural commodity, provided that sufficient actuarial data were available. The Government subsidizes up to 30% of the premium payments with the intent of covering all overhead costs. The subsidized premium should then be attractive to all risk neutral or risk averse growers. MPCI was first offered to cranberry growers in 1984. In the first year, there were only 22 participants out of an eligible population of about 800. In 1985, after premium rates

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were substantially reduced, 66 cranberry growers purchased MPCI (USDA).

The cranberry MPCI program works much like those for other crops. Participation is voluntary: each grower decides whether to purchase insurance to cover the crop of the coming year. For cranberries the decision must be made in autumn for the following autumn's crop. The per acre premium, expressed in units of yield (barrels), is the premium rate offered by the insurer multiplied by the guaranteed yield. The guaranteed yield is defined as the grower's average yield over the previous ten years (initially seven years for cranberries) multiplied by the guarantee level selected by the grower, either 50, 65 or 75% of average yield. In dollars, the insurance premium is the per acre premium above multiplied by the price per barrel selected by the grower. If as the result of an insurable event (and not, for example, bad management) actual yield falls below the guarantee level then the grower is entitled to an indemnity. The payment is equal to the difference between actual and guaranteed yields multiplied by the price election.

Premium rates differ by state and by yield class. Growers whose average yield puts them in a higher yield class enjoy a lower premium rate than growers in a lower yield class, although the former group usually pays a larger per acre premium. Examination of records of the population of growers held by the Cranberry Marketing Committee shows that the coefficient of variation of per acre yield declines with average yield, implying that the standard deviation is relatively unchanged (Dudek and Allen). A similar constancy of standard deviation has been found for corn and soybeans (Skees and Reed). Setting a premium rate that is a fixed percentage of average yield will lead to adverse selection. It would encourage the lower-yielding, higher-risk producers to purchase insurance coverage. At the same time, insurance would be less attractive to higher yielding producers who would be less likely to participate.

For the cranberry insurance program, the balance between aggregate indemnities and premiums over time is hard to determine. Its history is brief and, because fixed premium rates were used in the first year, the history may be complicated by adverse selection. In the cranberry program in 1984 $121,000 was paid in premiums and $64,000 was paid to growers in indemnities; in 1985 aggregate premiums were $185,000 and indemnities $36,000 (USDA).

## Risk Considerations and the Participation Decision

Farmers' subjective risk assessments may differ from historically based measures. Human judgment relies on selective perception, sequential information processing, and limited computational ability, none of which is helpful in assessing probabilities (Hogarth). Data-based calculations may ignore information available to farmers, for example changes in input rates. A few researchers have concluded that farmers can estimate expected yields quite accurately, finding no significant difference between actual and expected yields (Bessler; Grisley and Kellogg). Others have reached different conclusions. Pingali and Carlson, and Skees found that farmers underestimated yield, although no significance tests were reported. In contrast, Lee *et al.* discovered that all 15 of a group of growers overestimated income. Farmers appear to bias towards overoptimism when assessing variability in yield. Grisley and Kellogg, Skees, and Lee *et al.* observed consistent patterns of farmers underestimating yield variability or income variability. Bessler appears to have found exactly the opposite, although the test was on aggregated rather than individual data and compared shapes of distributions not variances. To growers both a subjective overestimate of expected yield and a subjective underestimate of variability work against their insuring: the levels of protection available appear to be too low and the premiums appear to be too high.

Objective measures could also be flawed. For example, if yields are trending upward a simple moving average will lag the trended value. The average will underestimate expected yield and overestimate variance of yield. When such a method is used to set insurance rates, as it was in the cranberry program, the rate is biased upwards, which will discourage participation.

A grower's willingness or ability to bear risk also affects the participation decision. Risk preference is commonly based on the Bernoullian conclusion that risk aversion can be represented by an expected utility function, u(x), where x is the quantity of money, income, or wealth. Arrow and Pratt have defined a degree of local risk aversion, the Arrow-Pratt risk aversion coefficient which is the ratio of the second and first derivatives of the Bernoullian utility function. That is, $r(x) = - u''(x)/u'(x)$. For a person whose expected utility is increasing and twice differentiable, Meyer (1977a, 1977b) has developed a criterion, stochastic dominance with respect to a function. It allows a decision maker's Arrow-Pratt coefficient to be determined from the decision maker's choices among distributions of risky outcomes.

The interval method described by King and Robison was used to bound the values of an individual's absolute risk aversion coefficient. There was one important difference: the context of the elicitation received more emphasis. The distributions of outcomes shown to decision makers were also wider in the present study. A distribution of net returns for a typical farm was divided into nine intervals of equal probability. The midpoint value of each area was taken as representative and the set of nine discrete values constituted the distribution representing a given strategy. A given pair of distributions represents equally likely outcomes from taking or declining to take crop insurance. The pair locates a specified boundary function in risk aversion-payoff space. In this study as in most others the boundary function is a risk aversion value that is constant over the entire outcome range. As Meyer points out (1977b, p. 483): "If for a particular pair of risky prospects, F(x) and G(x), one can find a [boundary function] k(x) such that the conditions of this [stochastic dominance with respect to a function] theorem hold, then this partially characterizes those who prefer F to G by the fact that they include all those more risk averse than k(x)." Also included in the group that prefers F to G are some individuals whose risk aversion measure varies and crosses the boundary within the range of outcomes. But by assuming constant risk aversion, agents are completely characterized. In the above context only those who are more risk averse than k(x) will prefer F to G. The tradeoff for presenting a more realistic context to the participant is that constant risk aversion must be assumed over a much wider range of outcomes.

**Data Collection**

Fifteen cranberry growers, all located in southeast Massachusetts, participated in the study. Growers were selected from volunteers at a growers' meeting and from suggestions made by the grower liaison officer of the grower cooperative. Although the sample was not random, an effort was made to make it representative of the locations and sizes of operations in Massachusetts. Whether a grower had ever purchased crop insurance was not considered. Each grower was interviewed twice with each interview taking at least an hour.

Each grower's subjective probability distribution of yield was extracted using two elicitation methods in successive interviews. At the first interview, conducted in February or March 1985, the judgmental fractile method (Raiffa) was used. By posing a series of questions, the range between the lowest and highest expected yields was first bisected into equally likely regions. Once the midpoint was set, the range from the lowest yield to midpoint was bisected, then the range from the highest yield to midpoint was bisected, and so on until eight equally likely yield ranges were established. At the second interview, conducted in late April or May, the visual impact method (Anderson, Dillon, and Hardaker) was used. Each grower was first instructed to try to make assessments with the same information that was available at the previous interview. The grower was then told to allocate chances, represented by 27 match sticks, to nine yields that were the end-points of the intervals determined at the first interview.

Each grower was asked on the first visit for a seven-year yield history. This was used to establish the operation's base yield and to place it in a risk class for insurance. If a grower was unable to provide a yield history beyond the minimum of three years that was required to be eligible for insurance, then a yield history was constructed by matching Massachusetts annual average yields with the grower's yield in the years available and then using this ratio to create yields for the missing years. This method appears to be that adopted by crop insurers to establish yields in the absence of historical records and had to be applied to about one-third of the growers in the sample. Where possible, growers' histories were verified with individual Cranberry Marketing Committee records or with delivery records from the grower cooperative.

Each grower's costs of production were estimated at the first interview. Growers were also asked how costs might be varied as an extremely good or bad yield was developing. The grower's assessment of cranberry price risk was also elicited at the first interview using the judgmental fractile method. For each operation, data from the first interview were later used to calculate distributions of net returns. The distributions were presented to each grower at the conclusion of the second interview.

Growers' risk preferences were elicited at the second interviews using the interval approach described by King and Robison. Participants were asked in a series of pairwise comparisons to indicate which of the distributions of cranberry incomes was preferred. In each pair of distributions one represented "insurance" and the other "no insurance." No measure was made of growers' levels of wealth. The Arrow-Pratt coefficient was assumed to be constant over the range of the distribution of incomes and the utility functions approximated by the exponential function, $U(y) = -(\exp(-ry))$, where r is the Arrow-Pratt coefficient and y is income. A standard set of distributions was presented to all full-time growers (more than 15 acres) and another to all part-time growers. The incomes in the full-time grower distributions ranged from a loss of $114,000 to a gain of $95,000 and for the part-time grower distributions from a loss of $6,000 to a gain of $44,000. Each choice the grower makes reveals a portion of absolute risk aversion space that is inconsistent with his or her preference. By posing successive choices, the space within which the grower's risk aversion coefficient might lie was narrowed.

## Results

### *Subjective Probability Distributions and Yield Histories*

The judgmental fractile method obtained intervals over the range of all conceivable yields. The intervals are equally likely outcomes but every value within an interval is not equally likely. Moments of the judgmental fractile subjective distribution were calculated using the midpoint of each interval (Table 1). Since these are population probability distributions, no degrees of freedom are lost in calculating the higher moments.

The subjective distribution obtained by the visual impact method is discrete since growers were presented with nine specific yields and asked to assign probabilities to each. The nine endpoints from the first interview were used rather than the eight midpoints because the midpoint of the lowest interval on every grower's judgmental-fractile-determined distributions was above the highest possible insurance guarantee level. Had the lowest midpoint value been used rather than the lowest conceivable value, a grower would have no way of indicating the subjective probability of a yield below the guarantee level. No grower

**Table 1. Probability Distribution of Cranberry Yields**

| | Subjective | | | | | | Historical | | |
|---|---|---|---|---|---|---|---|---|---|
| | Judgmental Fractile | | | Visual Impact | | | Seven Year Unadjusted | | |
| Grower Number | Mean | Standard Deviation | Skewness | Mean | Standard Deviation | Skewness | Mean | Standard Deviation | Skewness |
| 1 | 146 | 32.8 | −1.2 | 144 | 27.2 | −2.4 | 134 | 35.1 | 0.6 |
| 2 | 169 | 30.0 | −1.5 | 186 | 30.1 | −4.2 | 124 | 30.8 | −0.2 |
| 3 | 129 | 24.4 | −0.1 | 140 | 5.5 | −2.3 | 126 | 18.8 | 1.3 |
| 4 | 140 | 28.2 | −0.5 | 142 | 13.9 | 0.0 | 142 | 47.9 | −1.1 |
| 5 | 111 | 19.1 | −0.4 | 113 | 17.8 | −0.9 | 99 | 40.1 | 0.7 |
| 6 | 144 | 23.0 | −0.5 | 145 | 20.1 | −0.9 | 114 | 30.3 | 0.2 |
| 7 | 100 | 13.9 | −1.2 | 107 | 13.9 | −2.5 | 69 | 12.6 | 1.4 |
| 8 | 143 | 24.9 | −0.9 | 150 | 13.7 | 1.6 | 105 | 36.2 | 0.7 |
| 9 | 102 | 22.6 | −0.9 | 163 | 21.7 | −1.2 | 159 | 26.9 | 0.5 |
| 10 | 143 | 25.2 | −2.0 | 149 | 27.3 | −4.3 | 108 | 18.8 | 1.1 |
| 11 | 105 | 30.0 | −0.3 | 111 | 32.3 | 0.7 | 86 | 32.3 | 0.4 |
| 12 | 207 | 62.1 | −0.9 | 214 | 51.7 | −1.5 | 168 | 56.7 | −0.4 |
| 13 | 82 | 13.2 | −2.1 | 87 | 3.1 | 0.2 | 33 | 30.0 | 1.5 |
| 14 | 119 | 53.1 | −0.2 | 134 | 45.9 | −0.3 | 95 | 10.5 | 0.3 |
| 15 | 145 | 29.8 | −1.4 | 158 | 17.6 | 0.9 | 116 | 39.4 | 1.4 |

All measurements are in barrels/acre except skewness, which is the Pearsonian measure $[(x_i - x)/s]^3/n$.

assigned more than three chances in 27 to events below the 75% guarantee level; seven assigned one chance; five assigned none. Moments for the visual impact subjective probability distributions are shown in table 1. If the respondents had assigned probabilities equally to all interior values (as closely as the conditions of the experiment allowed) and half of the interior probability to each end point, then the moments of the second subjective distribution would have been almost identical with those of the first. Three of the 15 growers were able to achieve this consistency. Compared with the judgmental fractile method, distributions elicited by the visual impact method showed a higher expected yield for all but one grower, although almost half the sample altered expectations by less than 5%. Two growers displayed higher standard deviations with the visual impact method, caused by assigning a highly skewed or bimodal distribution to the given outcomes, but the large majority of respondents produced a tighter distribution with the second method.

There is no way to discover which method more accurately described growers' perceptions of yield risk at the time that insurance decisions were made. The time that elapsed between interviews could also have caused farmers to revise their beliefs, although both interviews took place after the insurance deadline but before the major perils to cranberry yields, spring frosts and insects, had been faced. Both distributions, by suggesting small benefit to insurance, were consistent with nonparticipation, the most common actual behavior.

A more important question in the participation decisions of growers is whether a grower's subjective yield distribution is different from the historical record used by insurers. Summary statistics for each grower's seven-year yield history are presented in Table 1. To compare growers' risk assessments with the historical records a separate test was performed for each grower. The subjective distribution of a grower was treated as if it were a hpothetical distribution. A one-sided test was used. The null hypothesis was that the seven historical observations could have been generated by the subjective distribution. Since a subjective yield higher than a historically based one discourages participation, the alternative hypothesis was that the cumulative distribution of the actual yields lies to the left of that of the subjective yields. Because of the small number of historical observations and possible skewness in the distributions, the Kolmogorov-Smirnov test was used (Siegel). For the judgmental fractile method the hypothesis of identical distributions was rejected at the 5% level in 11 of the fifteen cases (Table 2).

To assess the overall significance of the difference between a grower's subjective distribution and the historical distribution the grower-by-grower tests were pooled by the method of Pearson's $P_\lambda$ test (Maddala). Let $p_i$ be the probability for the ith grower of obtaining a coefficient as high as that reported given the null hypothesis is true. Then the hypothesis that there is no difference between subjective and historical distributions for all growers as a group can be tested with the statistic: $\lambda = \Sigma(-2 \ln p_i)$, which is distributed chi-square with 2k degrees of freedom, where k is the number of independent tests. The null hypothesis of identical distributions was rejected ($\lambda = 167.3$; 30 degrees of freedom, table 2).

Although subjective and data-based distributions are statistically different, they may be sufficiently similar in critical aspects. Participation should be unaffected if, first, the historical mean yield used by insurers to set the yield guarantee level is at least as great as the subjective mean. Second, the amount of risk built into the insurance premiums, measured as the variance of the historical distribution, must be at least as small as the variance of the subjective distribution. These one-sided tests were conducted for each grower as one sample tests using the moments of the subjective distribution as the parameter values. Rejection of either null hypothesis indicates a situation that discourages participation. At the 5% level, 8 of 15 growers had different means and 4 of 15 growers had different variances. Overall, according to Pearson's $P_\lambda$ statistic, the historical means and variances were significantly different from subjective values. Test statistics for the visual impact subjective distributions were even further into the critical region, a reflection of the higher means and lower variances elicited by this method.

A grower's subjective distribution of yield is dramatically different from the insurer's interpretation of that yield history. If the discrepancy explains why few cranberry growers have actually purchased crop insurance, then a transformation of the data that more closely matches the actual situation should improve participation rate. One prospective transformation is an adjustment based on the trend in individual yields.

*Yield trend adjustment*

Cranberry yields, like most other crop yields, have been trending upward over time (Morzuch *et al.*). As noted earlier, the insurance program uses a moving average of an operation's yield to account for a trend. If a trend is present, however, a moving average will always lag expected yield. An individual trend coefficient was estimated by regressing each grower's yield on time. Most of the operations displayed a positive time trend, but given the small sample of seven yield events for each grower, the trend coefficient was significantly different from zero ($\alpha$ = 0.05) in only three of the fifteen cases. When all of the individual tests in our sample were pooled, however, the null hypothesis of no yield trend was rejected by the Pearson $P_\lambda$ test ($\lambda$ = 52.02; 30 degrees of freedom). Trend coefficients and summary statistics for the adjusted yield histories are presented in table 3.

If adjusted yield histories more closely matched growers' subjective distributions then one disincentive to insurance participation would be reduced. Trend adjustments could be made at an aggregate level, though this would introduce another possible source of adverse selection. In a given yield class, operations with trends below the aggregate would find insurance more attractive than operations with trends above the aggregate. Although trends were difficult to establish at the individual level, each grower's yield history was adjusted by its time trend and the set of tests described for the unadjusted data repeated (table 2). Despite the impact of trend adjustment in reducing the discrepancy between subjective and actual means, there remains overall a significant difference between them. Also noteworthy is the overall significant difference in subjective and actual vari-

**Table 3. Cranberry Yield Trends, 1978–1982**

| Grower Number | Trend Coefficient (barrels/ acre/year) | Adjusted Historical Distribution[a] Mean | Standard Deviation |
|---|---|---|---|
| 1 | 6.5 | 160 | 32.15 |
| 2 | 8.0 | 157 | 25.45 |
| 3 | 7.6 | 156 | 9.28 |
| 4 | −5.2 | 121 | 46.58 |
| 5 | 7.2 | 125 | 38.52 |
| 6 | 9.3 | 151 | 22.82 |
| 7 | 3.4 | 83 | 10.18 |
| 8 | 9.4 | 138 | 32.31 |
| 9 | −5.6 | 140 | 25.29 |
| 10 | 5.0 | 128 | 15.33 |
| 11 | −7.7 | 55 | 31.98 |
| 12 | 12.3 | 217 | 50.16 |
| 13 | 10.6 | 76 | 19.56 |
| 14 | 4.3 | 113 | 4.84 |
| 15 | 15.2 | 169 | 27.93 |

[a] Mean and standard deviation are in barrels/acre.

**Table 2. Tests Comparing Subjective Distributions and Actual Samples**

| | Subjective Distribution: Judgmental Fractile | | Visual Impact | |
|---|---|---|---|---|
| | Actual Yields: Adjusted | Unadjusted | Adjusted | Unadjusted |
| Individual grower tests (n = 15) | Number of Hypotheses Rejected ($\alpha$ = 0.05) | | | |
| Same shape against actual lower | 11 | 9 | 12 | 9 |
| Same means against actual lower | 8 | 4 | 8 | 3 |
| Same variances against actual higher | 4 | 2 | 7 | 6 |
| Aggregate tests (df = 30) | Test Statistic ($X^2$) | | | |
| Same shape against actual lower | 167.3 | 102.3 | 280.4 | 176.2 |
| Same means against actual lower | 113.8 | 77.6 | 136.8 | 94.7 |
| Same variances against actual higher | 64.8 | 44.7 | 128.7 | 99.5 |

$X^2(30, 0.05) = 43.8$
$X^2(30, 0.01) = 50.9$

ances when, in the case of the judgmental fractile method, only two of 15 of the individual grower variances were significantly different.

### *Growers' Risk Preferences and Insurance Participation*

A grower purchases insurance to reduce variability in income rather than variability in yield. Income variability depends on the variances and covariances of yield, product price and costs. At least for cranberry production, yield variability dominates. Growers saw little opportunity to alter costs. During the first interviews they indicated that their production costs would be stable over the coming year and that they had little ability to reduce costs if they saw an extremely bad crop coming. All but two growers said that total costs of production could be reduced no more than 10% in the event of a disaster; six growers said that they could make no adjustment. Also at the first interviews growers said that they saw little price risk. Using the judgmental fractile method almost all of the growers said that they foresaw a range of cranberry prices that was less than 10% of expected prices.

Cranberry growers appear to be sufficiently risk averse to participate in an actuarially fair crop insurance program than would reduce risk (table 4). Ten of the fifteen growers (five of seven part-time growers and five of eight full-time growers) were found to be risk averse; three growers (one part-time and two full-time) were found to be approximately risk neutral; two growers (one part-time and one full-time) were found to be risk prone or preferring. If insurance premiums were subsidized to offset insurers' costs and insurers' and growers' risk assessments were consistent, then all risk averse growers would be expected to participate.

But, as earlier noted, insurers' and growers' risk assessments diverge. The final part of the analysis explored the impact of the differing assessments on participation. Using each grower's degree of risk aversion, costs of production and expected price for cranberries, each grower's optimal strategy was determined (table 5). For a given probability distribution of yield, if returns under insurance (75% guarantee level; $50 price election) stochastically dominated returns under no insurance for all possible values of the Arrow-Pratt coefficient for a grower, the grower would be expected to participate.

The first situation presented in table 5 is the one that actually prevailed in 1985. Three growers in the sample did purchase insurance, although one of them should not have according to his elicited risk preference. The second situation is the expected outcome if both the insurer and the grower had used the grower's seven-year yield history as the probability distribution of yield. Since it uses the 1985 premium rates and the insurer's method of calculating guaranteed yield, it is the result anticipated by the insurer, assuming that the

**Table 4. Risk Preference of Cranberry Growers**

| Grower[a] Number | Crop Area (acres) | Interval Containing Arrow-Pratt Risk Aversion Coefficient |
|---|---|---|
| 1 | 3.5 | (.000100, .000587) |
| 2 | 5.4 | (.000100, .000587) |
| 3 | 6.0 | (−.000001, .000100) |
| 4 | 7.5 | (−.000088, −.000001) |
| 5 | 8.0 | (.000013, .000100) |
| 6 | 9.0 | (.000013, .000100) |
| 7 | 10.0 | (.000013, .000100) |
| 8 | 15.0 | (.000013, .000100) |
| 9 | 17.5 | (−.000006, .000003) |
| 10 | 40.0[b] | (−∞, −.000019) |
| 11 | 25.0 | (.000018, .000052) |
| 12 | 27.0 | (−.000006, .000003) |
| 13 | 34.5 | (.000018, .000052) |
| 14 | 40.0 | (.000018, .000052) |
| 15 | 90.0 | (.000018, .000052) |

[a] Growers 1–7 are part-time cranberry growers and growers 8–15 are full-time.
[b] 23.0 producing acres.

**Table 5. Insurance Participation Under Different Yield Probability Distributions**

| Insurer Uses | Grower Uses | Number of Growers Insuring |
|---|---|---|
| Unadjusted historical | Actual decision | 3 |
| | Unadjusted historical (previous 7 years) | 7 |
| | Trend-adjusted historical | 10 |
| | Subjective | 6 |
| Trend-adjusted historical | Subjective | 8 |

grower's risk preferences have been correctly elicited. That only about half of the sample would have been expected to purchase insurance suggests that the subsidized rate is not actuarially balanced. In aggregate, farmers will pay more in premiums than they receive in indemnities. The subsidy was intended to overcome this bias. The third situation is the outcome if each grower had made an optimal decision using an individual trend-adjusted seven-year history. The fourth is if each grower had used the visual-impact-determined subjective distribution of yield. All of the above use the guaranteed yield calculated by the insurer's moving average method.

The final situation assumes that the insurer uses the individual grower trend adjustment to set guarantee levels (premiums were not changed) and the growers continue to use the visual-impact distributions. When growers' subjective distributions were used, the difference between their risk assessments and the insurer's was greatest. Changing the insurer's method of setting the yield guarantee levels to individual trend adjustments made a small improvement in participation rate but it could only partly overcome the impact of the divergent risk assessments.

## Conclusions

If our sample of growers is representative, about half of the growers in Massachusetts should have purchased insurance in 1985, a much greater rate than actually occurred. Had the insurers used trend adjusted historical yields to set the guarantee level, a further modest increase in participation would have been expected, a result that conforms with the findings of Zering *et al.* Trend adjustments to cranberry yields would raise insurance guarantee levels, increase indemnity payments, and make insurance more effective and appealing. Use of trend adjustments might be expected to increase the premium rate, though calculations performed by the authors as part of a study to revise the rate-structure indicate that the changes in rates would be small. At the conclusion of the second interviews, when distributions of net returns under "insurance" and "no insurance" options were discussed with each grower, three of the non-insurers expressed an interest in insuring, suggesting that ignorance of the consequences rather than lack of awareness of the program is a major reason for non-participation and this ignorance is more important than discrepancies in risk assessments.

At least for the crop and location examined here, the study casts doubt on the ability of growers to accurately assess yield distributions. If the growers' subjective distributions are regarded as true, then a reasonable adjustment to historical yield data, that of removing trend, does not produce a sample that is likely to have been drawn from the subjective distribution. The trend adjusted yields do not appear to belong to a population with the same mean and variance as the subjective distribution. Although after adjusting the historical series there is a notable increase in the number of growers with sample means and variances not significantly different from the subjective parameters, the improvement is illusory. Aggregate tests show that, overall, significant differences exist. Other studies that have compared actual and subjective distributions have not performed aggregate tests in this way and as a consequence may have erroneously concluded that decision-makers can accurately assess means and variances of yields and prices.

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